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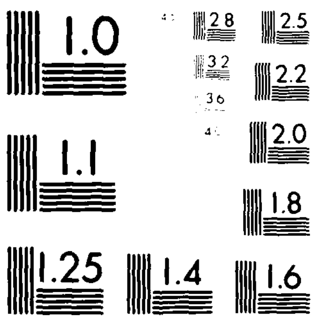

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FRANK J. SEILER RESEARCH LABORATORY

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INFLATION MODELING RESULTS FOR THE U.S. AND FOUR EUROPEAN COUNTRIES

FINAL REPORT

LT COL JOHN S. BRUSH

PROJECT 2304

AIR FORCE SYSTEMS COMMAND
UNITED STATES AIR FORCE

FJSRL-TR-80-0013

This document was prepared by the Applied Mathematics Division, Directorate of Aerospace-Mechanics Sciences, Frank J. Seiler Research Laboratory, United States Air Force Academy, Colorado. The research was conducted under Project Work Unit Number 2304-F1-64, The Development and Extension of Inflation Forecasting Models for Specific DOD Inflation Measures. Lt Col John S. Brush was the Project Engineer in charge of the work.

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This report has been reviewed by the Commander and is releasable to the National Technical Information Service (NTIS). At NTIS it will be available to the general public, including foreign nations.

This technical report has been reviewed and is approved for publication.

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Results of research to develop non-judgmental forecasting models of U.S. and selected European wage inflation are reported. Models are characterized in terms of economic content and forecasting improvement over trend models.

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I. INTRODUCTION

The report describes research conducted over the period of several years directed at developing non-subjective wage forecasting models for the U.S. and for four European countries. A requirement existed for models that could generate multiple year forecasts along with uncertainty ranges so that complex budget and planning decisions could be taken. Results of this research yielded models which appear to be improvements over trend projection approaches.

II. THEORETICAL CONSIDERATIONS

The problem of constructing forecasting models of wage inflation can be undertaken by many different approaches. Two of the most obvious are multi-sector coupled equation econometric models or, alternatively, single equation models. A decision that must be taken is the use of exogenous variables which require the use of future information. A second concern is the role of theory in the selection of model inputs. A third question concerns model structure.

The eventual use of wage inflation forecasting models and the question of the desire, or lack of it, to include subjective adjustments dictates the use of exogenous variables. A specific example will clarify the issue. Suppose that one desires a model that yields as an output a forecast change in wage inflation over the next year. Call this variable

$$DWI_{t+1}.$$

One might be inclined to develop or fit this model over historical data using as inputs current and past year values of other variables, perhaps including the output variable. For example, these variables may be this and past year changes in consumer prices - say:

$$DCPI_t \quad \text{and} \quad DCPI_{t-1}.$$

as well as this and past year changes in wage inflation - say:

$$DWI_t \quad \text{and} \quad DWI_{t-1}.$$

The specific model can be written as

$$DWI_{t+1} = f(DWI_t, DWI_{t-1}, DCPI_t, DCPI_{t-1}). \tag{1}$$

Contrast this to a model that includes next year's change in consumer prices:

$$DWI_{t+1} = f(DWI_t, DWI_{t-1}, DCPI_{t+1}, DCPI_t, DCPI_{t-1}). \qquad (2)$$

Since next year's consumer prices are likely correlated with next year's wage inflation, one might expect that in fitting these models, the second model, equation (2), which includes next year's consumer prices, will enjoy a better fit over the historical data.

Consider now the problem of using these models to forecast. The first model, equation (1), requires only known information to generate a forecast, specifically this year and past year wage inflation and consumer prices. Thus, non-subjective forecasts are possible. In contrast, equation (2) requires next year's change in consumer prices to produce a forecast of next year's wage inflation. In this example, next year's consumer price inflation is, in equation (2), an exogenous variable. Equation (2) thus produces conditional forecasts dependent upon specification of next year's consumer prices. If one has definite opinions about next year's consumer price inflation, one will find equation (2) useful in generating forecasts of next year's wage inflation. If one does not, the model is of limited usefulness for forecasting, although it may be useful for theoretical economic purposes.

This example illustrates the fact that the end use of a model determines the choice of admissable model structure. It is probably safe to generalize the situation by observing that exogenous variable models are useful in exploring relationships among variables, while non-exogenous variable models are most useful in non-subjective forecasting.

Turning to the question of the role of economic theory in model construction, we approach an area of long term controversy in empirical economics. Very briefly, it seems distasteful to use input variables that

seem to bear no relationship to the output variable. If there is a concensus view, it is probably that one runs less risk of mistaking spurious correlation twixt input variables and an output variable if there is some kind of economic rationale connecting the variables. Consequently, even the most fanatical empiricists are more comfortable if their results support or are supported by economic theory.

III. APPROACHES TAKEN AND RESULTS

Certain technical approaches aimed at minimizing problems of nonstationarity and improving forecasting accuracy were taken in this work. To a large extent these selections are manifest in the equations. For completeness they are summarized here.

All variables are expressed as percentage changes. Linear regression models are used. In model selection and search, quadratic non-linear approximations were explored. Serial correlation was investigated extensively and exploited where possible by the use of an iterative approach to first order error identification. A generalized least squares procedure [2] is used with percentage change data to detrend. Recent work by Park and Mitchell [3] points out the necessity of this approach. Although equal weighted least squares was used, exponentially decaying weight least squares was investigated by reserving a three year period for forecast tests. The short data length led to no conclusions. Recognizing that the degree of freedom problem inherent in a one year horizon model conflicted with the desire to exploit all of the quarterly data, a stacked observation scheme was used. Consequently corrections of R^2, standard error, and T-statistics for degree of freedom became complex. In practice no specific corrections were computed. Higher T-statistic criteria than usual were used to determine whether variables should be included. Reported standard errors are unadjusted for degrees of freedom. These reported standard errors are, of course, only part of the out-of-sample errors that can be anticipated in forecasting. Model mis-specification, non-stationarity, and the obvious fact that the error sequence upon which standard error is estimated may not be Gaussian all enter as potential error sources in forecasting.

A further decision was taken to use all data available without introducing dummy variables. This approach may result in biased estimates of coefficients, but enjoys the advantage of generating a more realistic standard error estimate. Since fairly long term forecasts were required, and past values of the independent variables were not helpful in generating forecasts beyond one year, a second model was built of each series which is simply a ARIMA (0,1,0) model using percentage changes as the variable. This permits a boot-strapping of forecasts beyond one year using a model specifically developed for this purpose. The data source for all European models was the OECD published data series. The data source for U.S. models is the Department of Commerce Survey of Current Business and the Employment and Earnings Statistics for the United States.

Belgium Hourly Rates in Manufacturing (OECD)

Data: 65.I to 78.IV

	R^2	d-w	$\frac{SE}{SE_{trend}}$
One year: $$\frac{w_{t+4}-w_t}{w_t} = \underset{(-0.86)}{-.009} + \underset{(12.02)}{.916}\,\frac{w_t-w_{t-4}}{w_{t-4}} + \underset{(5.66)}{.463}\,\frac{P_t-P_{t-4}}{P_{t-4}} - .29e_{t-1}$$	.60	1.84	$\frac{.033}{.050}$
One year link: $$\frac{w_{t+4}-w_t}{w_t} = .029 + .710\,\frac{w_t-w_{t-4}}{w_{t-4}} + e_t$$	.45	1.74	$\frac{.038}{.050}$

w_t = wage index in quarter t

P_t = industrial production index in quarter t

e_{t-1} = forecast error in quarter t-1

T-statistics in parentheses

All data in decimal percents 1% = .01

First equation estimated using iterative serial correlation corrections

Denmark Hourly Earnings Mining and Manufacturing (OECD)

Data: 65.I to 78.IV

	R^2	d-w	$\frac{SE}{SE_{trend}}$
One year:			
$$\frac{w_{t+4}-w_t}{w_t} = \underset{(7.34)}{.100} + \underset{(2.72)}{.407} \frac{C_t-C_{t-4}}{C_{t-4}} + .34\, e_{t-1}$$	.223	1.93	$\frac{.038}{.043}$
One year link:			
$$\frac{w_{t+4}-w_t}{w_t} = \underset{(4.63)}{.083} + \underset{(2.87)}{.368} \frac{w_t-w_{t-4}}{w_{t-4}}$$	.132	2.00	$\frac{.041}{.043}$

w_t = wage index in quarter t

C_t = consumer price index in quarter t

e_{t-1} = forecast error in quarter t-1

T-statistics in parentheses

All data in decimal percents 1% = .01

First equation estimated using iterative serial correlation corrections

Netherlands Hourly Rates Industrial, Male OECD

Data: 65.I to 78.IV

	R^2	d-w	$\frac{SE}{SE_{trend}}$
One year:			
$\frac{w_{t+4}-w_t}{w_t} = \underset{(0.79)}{.009} + \underset{(7.82)}{.738}\frac{w_t-w_{t-4}}{w_{t-4}} + \underset{(3.95)}{.285}\frac{P_t-P_{t-4}}{P_{t-4}} - .11e_{t-1}$	.518	1.99	$\frac{.027}{.038}$
One year link:			
$\frac{w_{t+4}-w_t}{w_t} = \underset{(2.53)}{.030} + \underset{(6.06)}{.670}\frac{w_t-w_{t-4}}{w_{t-4}}$	.405	1.63	$\frac{.030}{.038}$

w_t = wage index in quarter t

P_t = industrial production index in quarter t

e_{t-1} = forecast error in quarter t-1

T-statistics in parentheses

All data in decimal percents 1% = .01

First equation estimated using iterative serial correlation corrections

Norway Hourly Earnings Manufacturing (Males)

Data: 65.I to 78.IV

	R^2	d-w	$\frac{SE}{SE_{trend}}$
One year:			
$\frac{w_{t+4}-w_t}{w_t} = \underset{(3.56)}{.060} + \underset{(3.05)}{.687}\frac{C_t - C_{t-4}}{C_{t-4}} + .16e_{t-1}$	.197	2.00	$\frac{.046}{.051}$
One year link:			
$\frac{w_{t+4}-w_t}{w_t} = \underset{(4.30)}{.073} + \underset{(2.32)}{.322}\frac{w_t - w_{t-4}}{w_{t-4}}$	.091	2.09	$\frac{.049}{.051}$

w_t = wage index in quarter t

C_t = consumer price index in quarter t

e_{t-1} = forecast error in quarter t-1

T-statistics in parentheses

All data in decimal percents 1% = .01

First equation estimated using iterative serial correlation corrections

U.S. Hourly Earnings SCI 3721 Aerospace Workers

Data: 49.I to 78.IV

One year:

$$\frac{w_{t+4}-w_t}{w_t} = \underset{(4.18)}{.037} + \underset{(5.34)}{.399}\,\frac{C_t-C_{t-4}}{C_{t-4}} + \underset{(0.93)}{.058}\,\frac{G_t-G_{t-4}}{G_{t-4}} - \underset{(-1.20)}{.194}\,U_{t-4} + \underset{(3.69)}{.357}\,M_t - \underset{(-2.07)}{.186}\,\frac{w_t-w_{t-4}}{w_{t-4}} + \underset{(2.49)}{.180}\,\frac{w_{t-4}-w_{t-8}}{w_{t-4}}$$

R^2	d-w	$\frac{SE}{SE_{trend}}$
.520	2.03	$\frac{.018}{.026}$

One year link:

$$\frac{w_{t+4}-w_t}{w_t} = \underset{(6.82)}{.038} + \underset{(4.10)}{.36}\,\frac{w_t-w_{t-4}}{w_{t-4}}$$

R^2	d-w	$\frac{SE}{SE_{trend}}$
.125	2.13	$\frac{.024}{.026}$

w_t = SCI 3721 wage index in quarter t

C_t = consumer price index in quarter t

G_t = GNP nominal in quarter t

U_t = average unemployment rate for previous 4 quarters ending in quarter t (all workers) 3% = .03

M_t = percentage change in M1B over four quarters ending in quarter t. 10% = .10

Both equations simple linear regressions.

IV. TECHNICAL COMMENTS

The models reported in section III raise some interesting econometric and model identification issues. Note first of all that the serial correlation term for the four European countries' one year models is reported without a T-statistic. Because the observations were stacked and overlapping, the degree of freedom distortion enters in a complex fashion. Following [1], bounds upon the significance of this term can be taken by suggesting an analogy with the approximation for standard error in correlation coefficients as the reciprocal of the square root of the number of observations. On this criteria the standard error of the serial correlation term could range from .28 to .14. It would appear that the models for Belgium and Denmark enjoy a significant serial correlation term, while the case is weaker for the models for Norway and the Netherlands.

The one year link equations reported for all five models are simple but noteworthy. Consider how all have the form of a positive constant plus a coefficient (ranging from .33 to .71) times last year's inflation rate. Thus in all four countries, inflation is seen as subject to propagation at a decaying rate into the future. Caution is suggested in interpreting too much into these findings for the reason that we are looking at the output of what must be considered a non-stationary closed loop control system that uses a lagged output as an input. It is nonetheless interesting that in all cases increases in inflation in one year lead to further increases in inflation in the following year, and in no case to a reduction in inflation.

Note the similarity between the one year models for Belgium and the Netherlands. Future wage inflation is determined by past inflation and by past industrial production. In contrast, Denmark and Norway are best modeled by use of past consumer prices. This weak dependence on past wage

inflation is also reflected in the low R^2 for the link equations for Denmark and Norway.

The U.S. model is more complex than the European models. Note the presence of two significant lagged wage inflation terms and factors for nominal GNP growth, money supply growth, and the unemployment level. The low T-statistic for GNP growth might suggest its exclusion, but serial correlation problems then appear. It was judged easier to leave this term in rather than estimate a serial correlation term. It is satisfying to note the "correct" signs of the nominal GNP, money supply and unemployment terms in the face of the complex second order lag dependence on past wage inflation.

One might speculate that a U.S. model based on more recent data would forecast better than one based on data since 1949, but this model generated a forecast of 8.3% wage inflation for the four quarters ending 79.IV. The actual rate was 9.2%. This error of .9% compares favorably to the fitted standard error of 1.8%. Because of stacked observations and degree of freedom questions, a Chow test was not performed.

Perhaps the weakest aspect of the U.S. model is the use of the average unemployment rate of two years past. It may be an unintended proxy for a four year business cycle.

V. CONCLUSIONS AND EXTENSIONS

In conclusion, some observations on the use of these and similar models in actual program management are given. Obviously this empirical approach to forecasting inflation using simple single equation models lacks the satisfying theoretical structure of multiple equation multi-sector approaches.

This approach does have two properties that may make it more usable in real world financial control and decision making. First is that meaningful error limits can be attached to forecasts because of the non-subjective nature of the equations. It should be noted that virtually all traditional multiple equation forecasting agencies use both exogenous subjective variable inputs and further subjective adjustments and thus are unable to give meaningful descriptions of probable errors. Second is that multi-year forecasts can be made using the linking equations.

Consideration of these error ranges gives the decision maker a basis for evaluating various strategies in financial management. It is self-evident that such ranges are more meaningful than point estimates.

All of these models could be improved. Section III listed some alternative approaches tried, but there are others. Most interesting is the possibility of developing a Kalman filter based non-stationary model. There is at present insufficient data to justify this approach. As time passes and more data are accumulated, this will become more attractive. Such a model, if carefully constructed, could track changes between inputs and outputs and avoid the inevitable bias problems of traditional regression approaches.

Another possibility is to develop a joint forecasting approach combining subjective and non-subjective inputs. It is not clear how the essential stability of the subjective input is going to be established, but the possibility is intriguing.

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